

ARTIFICIAL NEURAL NETWORK AND PARTICLE SWARM OPTIMIZATION HYBRID INTELLIGENCE FOR PREDICTING CUTTING FORCE DURING HARD TURNING OF H13 TOOL STEEL WITH MINIMAL CUTTING FLUID APPLICATION

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ABSTRACT

The manufacturing industry in the modern era is striving and thriving hard to be cost competitive and efficient by employing innovative techniques. One such strategy which can make improved operational performance is hard turning. Hard turning process allows a shop floor to turn heat-treated workpiece with hardness over 45 HRC directly to the final size and shape. Hard turning requires a huge supply of cutting fluid to enhance its cutting performance. Petroleum-based emulsions are in regular use for metal cutting as these fluids improve the quality of the finished products and increase productivity by cooling and lubricating but their uses are being questioned nowadays as they create several environmental and health issues. Hence, from the ecological and health point of view, dry machining is the best logical alternative as it is free from the health issues related to operators in the shop floor and the contamination of water and air. However, dry machining is not efficient for many metal cutting operations as it affects surface finish and reduces tool life. Under such circumstances, the concept of minimal cutting fluid application (MCFA) proves itself as a possible solution. The present study aims to investigate the effect of minimal cutting fluid application while hard turning of H13 tool steel. An Artificial Neural Network (ANN) model was developed for the prediction of cutting force and its ability to predict cutting force (F_z) was analyzed. An effort has also been made to optimize the cutting parameters using Particle Swarm Optimization (PSO) to achieve minimum cutting force.

KEYWORDS: Minimal Cutting Fluid Application (MCFA), Artificial Neural Network (ANN), Cutting Force (F_z) & Particle Swarm Optimization (PSO)

Received: Jun 19, 2018; **Accepted:** Jul 10, 2018; **Published:** Aug 02, 2018; **Paper Id.:** IJMPERDAUG201896

INTRODUCTION

The industrial and manufacturing sector keep evolving newer methods and techniques to improve product quality to deliver top quality products in the most effective and economical manner [1]. In the recent years, hard machining has acquired considerable importance in the field of metal cutting. Hardened steels offer greater durability and wear resistance, making it well-suited to heavy-duty applications in the field of automotive and die tool industry [2]. Due to the advancement in cutting tool materials, the rigidity of machine tools and special tool holders, hard machining has become accessible to any machine shop and seems to be an appealing option over conventional machining techniques [3]. Hard turning uses a large amount of cutting fluid to enhance cooling and lubrication in order to reduce friction and heat developed during machining. The present regulations with regard to

sustainable and environmentally safe processes and practices put more strain on the manufacturing process. In this endeavor, many researchers considered it a challenge to devise new ways of solving such issues. The elevated temperature that exists at the cutting region during hard turning instantly boils and vaporizes a portion of cutting fluid and produces harmful fumes that cause harmful effects to the workers in the shop floor and causes environmental pollution [4].

With the advent of new standards regarding the environment, health and safety, some of the ingredients in many of the cutting fluids were identified as problematic. Due to such health issues, a number of government agencies have established regulations and standards for particulate exposure. For example, the Permissible Exposure Level (PEL) for cutting fluid aerosol concentration should be maintained within 5 mg/m³ as per the Occupational Safety and Health Administration (OSHA) of United States and is further recommended to reduce the PEL value to 0.5 mg/m³ [5].

Cutting fluid usage, storage and disposal affect the cost-effectiveness of the machining processes. Industries spend 7% to 17% of the production cost of cutting fluids [6]. Under such situation, dry machining is a possible alternative but it requires machine tools and cutting tools that can take enormous cutting forces. Hence, such a scheme cannot be executed as such in the existing shop floor. During dry machining, a huge amount of vibration is produced which affects the tool life as well as product quality and also will lead to premature tool failure. Dry machining increases the temperature in the cutting region. This high temperature causes excessive tool wear and dimensional errors at the workpiece [7].

For reducing the aforesaid negative impacts of cutting fluids, techniques MQL and MCFA were developed. MQL technique reduces consumption of cutting fluids to a greater extent. It promotes a reduction in cutting force, improves surface finish and dimensional accuracy [8]. Formation of a large amount of mist is one of the major constraints of MQL method, which extends the risk of aerosol in the shop floor environment [9, 10] but MCFA system excludes the role of compressed air from the system and supplies cutting fluid in the range of 2 to 10 ml/min directly at the critical contact zones [11]. Uzi Landman [12] narrated that the frictional forces between two sliding surfaces can be decreased to a greater extent by fluctuating the width of the lubricant bridging the gap using pulsed delivery. In the MCFA method, cutting fluid is delivered at very high velocity directly to the cutting zone with the help of an injector in a pulsating manner which enables the MCFA method to achieve a reduction in cutting force. In every practical sense, MCFA method looks like dry machining and at the same instant, it is exempted from the drawbacks connected with conventional wet machining [13, 14].

Some of the researchers explored the performance MCFA system during milling and turning of hardened steels. The results proved the enhancement in operational efficiency in terms of decrease in cutting force and vibration, enhancement in tool life and surface quality when compared to flood cooling and dry machining [14 - 17]. So as to get accurate and improved results, analytical models are usually caused to undergo assumptions and simplifications. For real-time applications, Artificial intelligence based modeling approaches are often preferred. In that, ANN has proved itself to be attractive, consistent and practicable [18 - 19]. ANN model was employed by Ozel and Karpat during finish hard turning to predict flank wear and surface finish [20]. A model based on ANN was developed by Leo and Varadarajan to predict surface roughness during milling of hardened AISI4340 steel with MCFA technique [21].

From the literature, it was observed that a lot of research works have been reported on hard turning of different steels in order to minimize cutting force and surface roughness but no work is reported on the prediction of cutting force using ANN while hard turning of H13 steel with MCFA technique. In this research, a hard turning process was assisted with MCFA technique, which reduced the quantity of cutting fluid to a minimum amount of 8 ml/min. Based on the earlier

researches in the optimization during machining of hardened steels, an effort was also made to optimize the cutting parameters using particle swarm optimization [22 – 27] to achieve minimum cutting force. The prediction model derived out of ANN was found to be highly accurate with more than 99% accuracy.

SELECTION OF WORKPIECE AND CUTTING TOOL

A cylindrical bar of H13 tool steel with a hardness of 45 HRC and diameter 70 mm × 360 mm long was used as the workpiece material in this investigation. The chemical composition of H13 tool steel is given in table 1.

Multicoated (TiC and TiCN) inserts with specification SNMG 120408 (MT TT5100) and the tool holder with specification PSBNR 2525 M12 were used for machining the workpiece.

Table1: Chemical Composition of H13steel (Weight %)

C	Mn	Si	P	S	Cr	Mo	Fe
0.430	0.214	1.08	0.0330	0.0290	5.02	1.13	Balance

EXPERIMENTATION

Figure 1 shows the experimental setup developed for this investigation. An all geared Kirloskar Trunmaster-35 lathe with variable speed and feed drive was utilized for machining. The cutting speed and feed rate were independently controlled using separate variable DC speed /feed controllers.

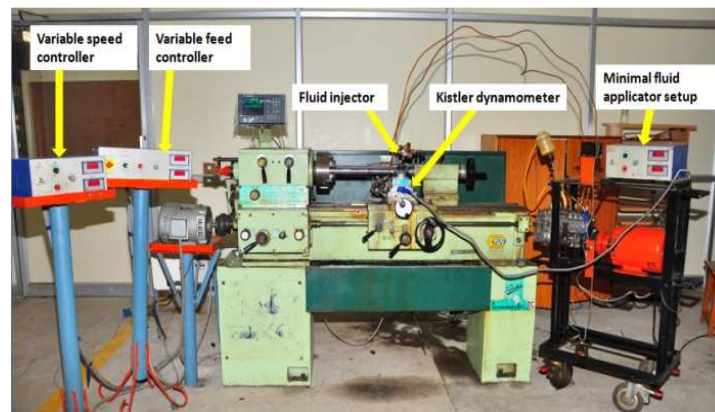


Figure 1: Experimental Set-up for the Hard Turning of H13 Steel

Kistler multi-component (piezoelectric) dynamometer (9257B) with a multichannel charge amplifier (5070A) along with the data analysis system (DynoWare) was used for the measurement of cutting force. Preliminary experiments were carried out for fixing the upper and lower limits of cutting parameters. Based on the results from the preliminary experiments, cutting speed was fixed between 77 and 115 m/min. The feed rate was fixed between 0.05 and 0.1 mm/rev and the depth of cut was fixed between 0.5 and 1 mm. The fluid application parameters were kept constant. Accordingly, the pressure at the injector nozzle was kept at 100 bar, frequency of pulsing at 500 pulses/min, a quantity of application at 8 ml/min and composition of cutting fluid emulsion as 20% of oil in water [28]

The cutting experiments were designed and conducted based on the five-level central composite rotatable design with full replications. Table 2 shows the five levels of cutting parameters.

Table 2: Five Levels of Cutting Parameters

Cutting Parameters	Levels				
Cutting Speed (m/min)	77	85	96	107	115
Feed Rate (mm/rev)	0.05	0.06	0.07	0.09	0.1
Depth of Cut (mm)	0.5	0.6	0.75	0.88	1

Table 3 shows the design matrix.

Table 3: The 3-Factors 5-Level CCD Matrix with the Observed and the Predicted Responses

Run Order	Type of Data	Cutting Speed (v) (m/min)	Feed Rate (f)(mm/rev)	Depth of Cut (d) (mm)	Cutting Force (N)		
					Experimental	Predicted using ANN	% Error
1	Training	85	0.06	0.6	211.8	226.1544	6.777337
2	Training	107	0.06	0.6	248.2	248.1576	0.01708
3	Training	85	0.09	0.6	250	249.9963	0.00148
4	Training	107	0.09	0.6	260.7	260.5900	0.04219
5	Training	85	0.06	0.88	228	236.9978	3.946404
6	Training	107	0.06	0.88	240	240.0083	0.003458
7	Testing	85	0.09	0.88	318	330.9540	4.073585
8	Training	107	0.09	0.88	321	321.0016	0.000498
9	Training	77	0.07	0.75	245.3	245.2117	0.036
10	Training	115	0.07	0.75	254	252.6738	0.52213
11	Training	96	0.05	0.75	239.3	239.3084	0.00351
12	Training	96	0.1	0.75	345	344.9378	0.01803
13	Training	96	0.07	0.5	202.7	202.6783	0.01071
14	Testing	96	0.07	1	281.5	271.5281	3.54242
15	Training	96	0.07	0.75	276.5	277.2897	0.285606
16	Training	96	0.07	0.75	277.3	277.2897	0.00371
17	Training	96	0.07	0.75	276.5	277.2897	0.285606
18	Training	96	0.07	0.75	277.1	277.2897	0.068459
19	Training	96	0.07	0.75	277.5	277.2897	0.07578
20	Testing	96	0.07	0.75	278.1	277.2897	0.29137

NETWORK ALGORITHM FOR ANN

The literature review revealed that Artificial Neural Network is a preferable algorithm for developing a predictive model for complex nature of the hard turning of H13 steel. Accordingly, the Artificial neural network was developed and trained using Lvenberg-Marquardt Algorithm (LM) and cutting force values were predicted. The best configuration for predicting cutting force was selected by considering the configuration which gave the least MSE error with the better coefficient of determination. This was accomplished by altering the number of hidden layers into single and multilayer types and by changing the neuronal values of the hidden layer(s). The nodes in the hidden layer were altered on the basis of “n/2”, “1n”, “2n”, and “2n+1” where n is the number of nodes in the input layer and in order to obtain the best configuration of the network. The number of hidden layers was also altered on the basis of trial and error method [29].

The tangent sigmoid (Tansig) transfer function was considered for the hidden layers in this experimentation and is shown in equation (1)

$$F(x) = \frac{1}{1 + e^{-x}} \quad (1)$$

In order to get the best possible network structure, ANN model was trained with 80 different network

configurations. A few of the network configurations which provided lower values of RMSEs are shown in Figure 2. Based on the results, 3-4-1 network structure was selected with Multilayer Normal Feed Forward algorithm.

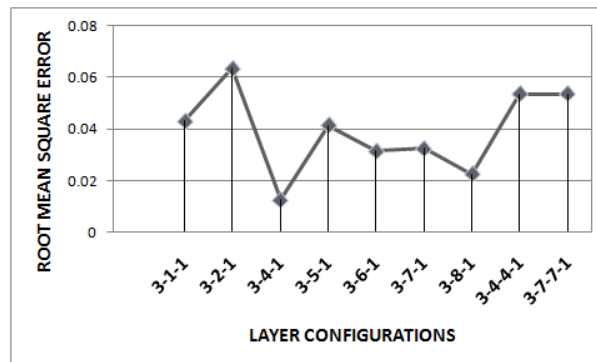


Figure 2: ANN Layer Configurations with Limiting RMSE Values

Figure 3 shows the ANN model consists of one input layer with three neurons corresponding to cutting speed, feed rate and depth of cut, a hidden layer with four neurons and an output layer corresponding to cutting force.

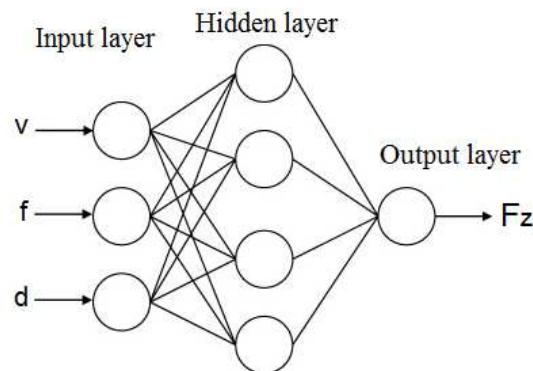


Figure 3: The 3-4-1 Network of the ANN Model

The regression coefficient (R) value of 0.99996 was obtained for the 3-4-1 network configuration, which is very close to unity and it shows a close relationship between observed and predicted data. Table 3 shows the experimental and predicted data.

Figure 4 shows the graphical representation of the correlation between experimental and predicted values of cutting force.

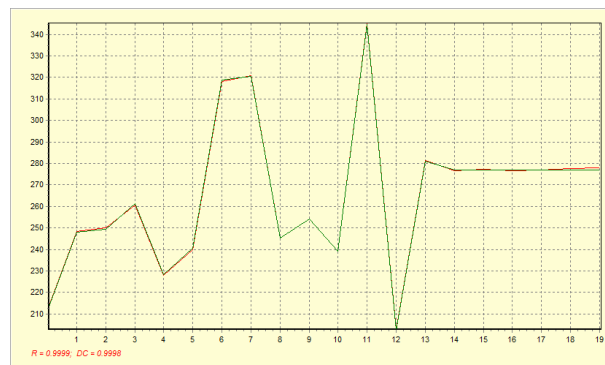


Figure 4: Correlation between Experimental and Predicted Values

OPTIMIZATION USING HYBRID ANN-PSO

In this study, an effort was made to find the optimum values of cutting parameters to get the least possible cutting force within the specific test range. A hybrid ANN-PSO approach was developed to solve the optimization problem for this study. The predictive model was trained and developed [30]. The developed Artificial Neural Network (ANN) was used as the fitness function for Particle Swarm Optimization (PSO). Particle Swarm Optimization is a population-based optimization technique inspired by the social behavior of bird flocking.

The machining parameters leading to minimum cutting force is the optimization problem in this case. The constraints in this case are cutting speed (77 m/min - 115 m/min), feed rate (0.05 mm/rev - 0.1 mm/rev) and depth of cut (0.5 mm - 1 mm). The PSO parameters used were population size of 20, inertia weight 0.1 and learning factor of 2.

The optimum machining parameters leading to minimum cutting force obtained using hybrid ANN-PSO approach is given in Table 4. The optimum cutting force value obtained was 195.51122 N. The optimum machining parameters obtained using hybrid ANN-PSO approach are cutting speed = 77.059775 m/min, feed rate = 0.050999 mm/rev and depth of cut = 0.502636 mm.

Table 4: Optimum Machining Parameters using the Hybrid ANN-PSO Approach

Machining Parameter	Optimum VALUE
Cutting Speed (m/min)	77.059775
Feed rate (mm/rev)	0.050999
Depth of cut (mm)	0.502636

Confirmatory tests were conducted to check the adequacy of the optimum parameter combinations and the experimental results showed good agreement with the predictions. The confirmatory test result is shown in Table 5

Table 5: Confirmatory Test Results

Optimum Cutting Force (F_z) Predicted through ANN-PSO Approach (N)	Confirmatory Experimental Result F_z (N)	% Error
195.51122	198.076	1.2948

RELATIVE SIGNIFICANCE OF EACH PROCESS PARAMETERS

Among the three process parameters, depth of cut and feed rate were found to have the significant influence on cutting force. Feed rate contributed 48% to cutting force. Similarly, depth of cut and cutting speed contributed 47% and 5% respectively, on cutting force. The relative significance of each process parameters is graphically represented in Figure 5. The influence of feed rate and depth of cut on cutting force is graphically represented in Figure 6.

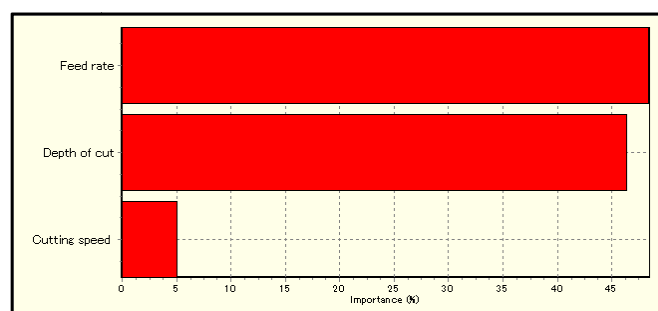


Figure 5: Relative Significance of Process Parameters on Cutting Force

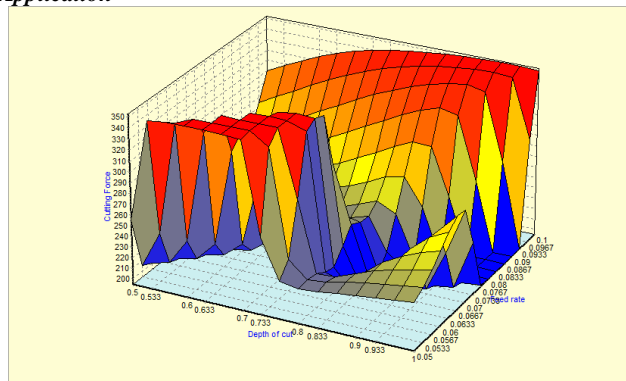


Figure 6: Influence of Depth of Cut and Feed Rate on Cutting Force

CONCLUSIONS

The present investigation revealed the following conclusions

- The developed ANN model can be utilized in an automated hard turning of AISI H13 steel with a minimal fluid application for fixing the cutting parameters in order to reduce the cutting force and power consumption to achieve best results within the tolerance limits.
- MCFA scheme can be directly implemented on the shop floor as it does not involve any major alterations in the existing setup.
- Hybrid ANN-PSO approach can be effectively used for optimizing cutting parameters to achieve minimum cutting force.
- MCFA technique can be used to promote the green and clean environment in the shop floor, as it reduces the health hazards associated with the large-scale usage of cutting fluid.

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